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30 July 2015

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July 30, 2015

Abstract

In an effort to accommodate a change in the U.S. Federal Highway Administration's goals towards "race-neutral methods" concerning the involvement of Disadvantaged Business Enterprises in procurement contracting, the Texas Department of Transportation created a Learning, Information, Networking and Collaboration (LINC) bidder training program. We examine the costs, benefits, and efficacy of this program using ten years of data, employing firm-specific bidding patterns with participation dates. We distinguish between ineligible firms as well as eligible firms that undergo training and those that don't, to consider a number of different empirical models which allow for potential asymmetries across these bidder groups.

JEL Classification: D44, H57, R42.
Keywords: auctions, bidder training, disadvantaged business enterprises.

*We are grateful to Jorge Balat, Tim Dunne, Philippe Gagnepain, Matt Gentry, Brent Hickman, Han Hong, Fabio Miessi, Jimmy Roberts, and Steve Tadelis for valuable discussions at different stages of this project. We would also like to acknowledge participants at the International Conference on Contracts, Procurement and Public-Private Agreements, the International Industrial Organization Conference, the Workshop on Procurement and Contracts at the University of Mannheim, the Brazilian Conference Series on Public Procurement and Concession Design, the Lancaster University Conference on Auctions, Competition, Regulation, and Public Policy and seminar participants at Copenhagen Business School, Maastricht University, Oberlin College, the University of Guelph, the University of Maine, and the University of New Hampshire for helpful comments. Lastly, we thank the Texas Department of Transportation for providing the data. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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1 Introduction

The U.S. Federal Highway Administration (FHWA) has used government policies since at least the early 1980's to encourage minority participation in procurement contracting. Many states employ bid preference programs, which discount the bids of qualified firms for the purpose of evaluation. Other programs require government agencies to set aside a certain percentage of a contract to be subcontracted out to disadvantaged business enterprises (DBEs) or other qualified firms. Over the decades and largely in response to court decisions (see, for example, the Supreme Court's 1999 ruling in *Adarand v. Peña*, U.S. Report 515 U.S. 200), the nature and administration of DBE programs has changed. While they still retain their basic structure, the goal of firm participation is now described as being "aspirational." Individual state agencies that administer the programs, are asked to achieve as much of the goal as possible by "race-neutral methods" before employing other race-conscious policies. For example, qualified DBE firms are not simply determined by belonging to a particular demographic group (e.g., being owned by a minority, veteran, or woman) but also by their economic circumstances (e.g., small businesses). The overall regulatory response of the FHWA was to tailor programs to meet the Court's objections.

In response to the shift in the disposition of FHWA policy, the Texas Department of Transportation (TxDOT) created its own Learning, Information, Networking, Collaboration (LINC) training program in 2001 to mentor eligible firms interested in doing business with TxDOT.[1] Texas has the second largest state economy in the U.S. and a diverse population with 37.62% of its residents identifying as Hispanic and 11.94% as Black in the 2010 Census. The intent of the LINC program is to maintain and support the role qualified firms play in the TxDOT procurement process by providing information, networking opportunities, project management, and training sessions. The program allows firm owners to improve their knowledge and project management skills, thus, increasing the chances for success without explicitly constraining the decision-making process. During our ten-year sample period which spans September 1997 to August 2007, the total value of contracts awarded to LINC-eligible bidders

[1] LINC was established as an opportunity for DBEs as well as historically underutilized businesses (HUBs) and small business enterprises (SBEs).

was \$2.04 billion. We examine the impact of the LINC program on participation, bidder behavior, chances for success, and the cost structure of qualified bidders acting as primary contractors. The LINC program description states that the targeted firms are "critical to economic competitiveness in the Transportation industry." As such, we also consider whether the LINC program might improve retention of such firms in the long-run for this industry.

We find the most convincing effects LINC has on bidders is with respect to bidding behavior—LINC-trained bidders behave more aggressively than firms that are not eligible for the program as well as those that are eligible but have not undergone the training program. In addition, the interest of a LINC-trained firm in a project generates an indirect competition effect in which ineligible firms (our most frequently-observed class of bidders) behave more aggressively than they otherwise would have. The lower bids carry through to generate cost-savings for TxDOT in two ways: first, when LINC-trained firms win their bids are lower, on average, than those of all other firms. Second, when other firms compete at auctions which attract interest from LINC-trained firms, the average winning bid is also lower. These two channels generate substantial savings for the state—even our most conservative estimates involve millions of dollars saved. We find LINC-trained firms that then win auctions maintain similar Lerner indexes to other firms. Moreover, eligible firms that do not get trained are more likely to exit the industry than firms that are not eligible, but this effect goes away for firms that graduate from the LINC program.

The efficacy of other class-specific preference policies on procurement costs have been examined by a number of researchers with varying conclusions. Several papers deal with bid preference schemes.[2] Denes [1997] compared bids submitted between solicitations restricted to small businesses and unrestricted solicitations, finding that bids are no higher in restricted settings. Marion [2007] found that in data from California auctions for road construction contracts, the price paid by the state was 3.8 percent higher for auctions which used preferences. Krasnokutskaya and Seim [2011] also analyzed bid preference programs in California highway procurement contracts and found that the preferential

[2] Note that the effect of such programs on the state's cost is ambiguous even at the theoretical level; see McAfee and McMillan [1989] and Hubbard and Paarsch [2009].

treatment of small businesses creates losses in efficiency but no change in the overall cost of procurement.

While bid preference policies introduce an asymmetry among bidders (even if bidders draw costs from the same distribution), the potential for efficiency distortions stems from a different source for programs setting minority subcontracting goals. These programs are often used in federal procurement contracts and may constrain the make-or-buy decision of prime contractors. Distortions may occur because of potentially less efficient production of tasks by subcontractors compared to the prime contractor (relative to an unrestricted setting) or due to changes in competition intensity in the subcontracting market. Marion [2011] used data from the California Department of Transportation to show that the subcontracting goals set for highway construction contracts in California raise DBE usage significantly, so that the constraints appear to bind. In fact, Marion [2009] found that after California's Proposition 209 was passed (which prohibited DBE subcontracting goals concerning race or gender), state-funded contracts realized a 5.6 percent fall in prices relative to federally-funded projects which still involved subcontracting goals. De Silva et al. [2012] evaluated the impact of a federal subcontracting policy years after its original implementation and found that minority subcontracting goals have not increased the procurement cost in Texas.

To our knowledge, we are the first to study the effects of a bidder-training program. We have contacted representatives at every U.S. state's Department of Transportation office and have learned two things: first, these programs are quite common as more than thirty states have in place a program with many of these elements; second, Texas seems to be one of the first states to introduce such a program and its program seems to be one of the largest in terms of participation. In our correspondence with employees at state offices we have learned that these programs often go by different names (e.g., Calmentor in California, Connect2DOT in Colorado, and Mission 360^o in Rhode Island) and are often defined as mentor-protégé programs which are administered through economic or local development offices. Most programs have bidder training, formal mentoring, educational seminars, outreach components such as trade shows and business fairs, technical assistance, financial and management consulting services, and/or networking as key elements. Nearly all programs have goals of promoting effective business development by improving the performance of trained firms, ultimately hoping for a higher survival rate of such firms.

In general, such training programs seem to be on the rise. Some states have either implemented new programs (e.g., the Oklahoma Department of Transportation's Small Enterprise Training Program) or are re-emphasizing or revamping old programs (e.g., the Washington Department of Transportation recently expanded its program from targeting minority- and women-owned firms to include small businesses in general), and a number of representatives for states that do not currently have any programs indicated that they felt such opportunities would be a good idea. Moreover, these programs are not unique to Department of Transportation—the leading inspiration for such programs seems to be the Stempel Program for the Port of Portland in Oregon.[3] Given the prevalence and interest in such training programs, we hope our work has important policy implications as there is potential for our findings to suggest alternative policies to meet the FHWA's original goals in a way that can actually generate clear cost savings (benefits). The only costs for the state are administrative salaries and expenses associated with organizing LINC-related sessions. We have obtained expense data that reports LINC costs for fiscal years 2005 to 2012 which show that the program costs the state about $200,000 per fiscal year.[4] In what follows, we hope to shed light on the potential benefits to be had from such a program either through participation, bidding, efficiency improvements, and/or firm retention.

In the next section, we describe our TxDOT data and first examine what drives a qualified firm to participate in the program. In Section 3, we investigate whether trained firms are more likely to bid on a contract once they hold the plans, as well as whether they are more likely to win a contract given they've chosen to bid. Linking the former probability concerning a firm's choice with the latter probability which involves an outcome is firm behavior. As such, we present a number of empirical models to document and help us interpret observed bidding patterns. Importantly, we can identify how bidding changed after program completion and evaluate effects the LINC program has had on winning

[3]See the very informative Wisconsin Department of Transportation [2010] report which summarized and surveyed how such programs have been operated in the U.S. and the Associated General Contractors of America's website: http://www.agc.org/cs/industry_topics/additional_industry_topics/the_stempel_plan for additional details on such programs.

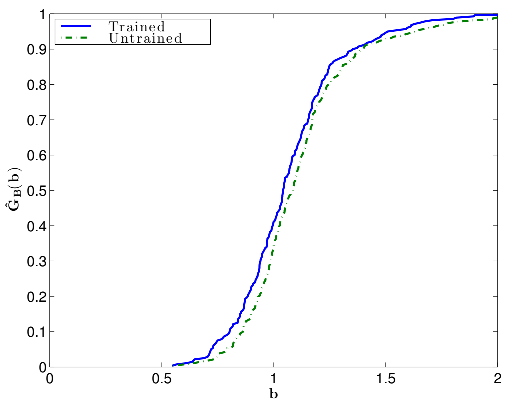
[4]The costs range from a low of $181,078 to a high of $235,234.

bids. Given what we can observe in the data, we also explore other ways in which LINC training might have changed firm behavior which have some backing in the auctions literature. Because these dimensions do not suggest changes that result from LINC, we consider whether something we cannot directly observe in the data might have changed in an important way. Specifically, in Section 4, we present a structural model which allows us to speak about potential changes to firms' (unobserved) cost structures, the efficiency of the auctions, and market power in the industry. The results and insights from such estimates live in Section 5. LINC-eligible firms have lower average costs and their cost distributions (trained or untrained) are significantly different from ineligible firms. However, when comparing distributions within the group of LINC-eligible firms, we do not find a statistical difference in the latent distribution of costs based on whether the firm is trained or not. In Section 6, we consider whether firm survival in the industry has been affected by participation and, lastly, in Section 7, we summarize our work and conclude.

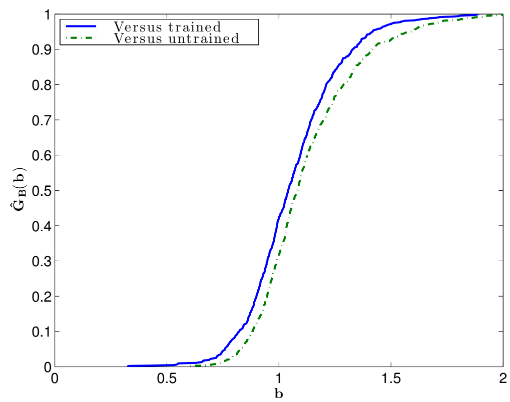
2 The LINC Program

Our primary focus is on how the bidding behavior might change as a result of the LINC program. A snapshot of bidding patterns observed in the data helps motivate this investigation. In Figure 1, we present four subplots containing empirical distribution functions of relative bids—the observed bids submitted by the firms normalized by the state's engineering cost estimate for the project. We condition on the engineer's estimate so that the bids are at least comparable across auctions. Auction theory says that bidding behavior changes with the number of participants at auction. As such, we restrict data for this set of figures to auctions for which we observe five bidders tendering offers. Keep in mind that, at procurement auctions, low bids are (aggressive behavior is) good for the state which is seeking to have a task completed at the lowest possible cost. The subplots leverage distinctions in the class of the competing firms based on whether they are eligible for and whether they participated in the LINC program by the time their bids were tendered.

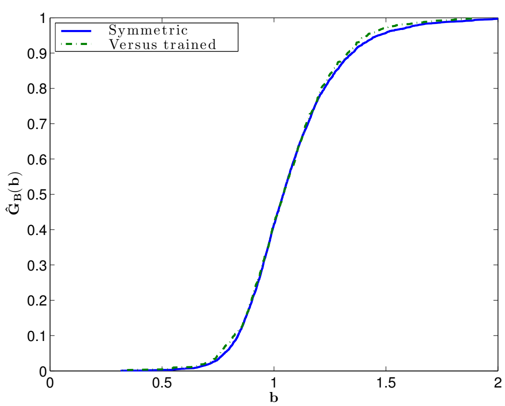
In subplot 1a, we consider the behavior of firms that are eligible for the LINC program at five-bidder auctions. The subplot suggests that LINC-trained firms behave more aggressively than untrained firms.



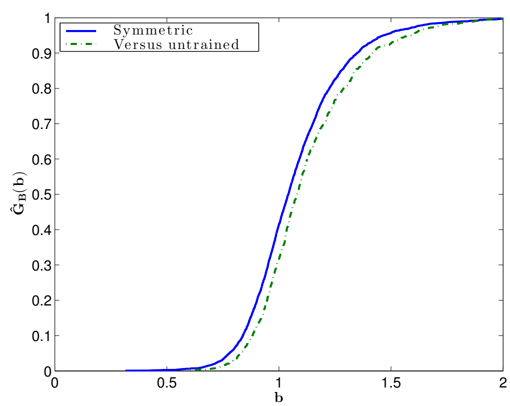
(a) Qualified Firm Behavior



(b) Ineligible Firm Behavior



(c) Ineligible Firm Behavior: Symmetric vs. Asymmetric with Trained



(d) Ineligible Firm Behavior: Symmetric vs. Asymmetric with Untrained

Figure 1: Relative Bid Distributions for $n = 5$

In contrast, in subplot 1b, we consider the behavior of firms that are not eligible for the LINC program and consider how they behave at auctions involving other ineligible firms along with at least one LINC-eligible firm. The figure suggests that these firms behave more aggressively when a LINC-trained firm is present at auction than when an eligible, but untrained firm is present. In subplots 1c and 1d, we consider again only the behavior of ineligible firms, but compare their bids at symmetric auctions (comprised only of ineligible firms) with their behavior at asymmetric auctions (comprised of ineligible firms and at least one LINC-eligible firm). Subplot 1c, shows that if the auction is asymmetric because a LINC-trained firm is present, behavior is not distinguishable from behavior at symmetric auctions. However, subplot 1d, shows that if the auction is asymmetric because a LINC-eligible, but untrained firm is present, bids of ineligible firms are less aggressive than their behavior at symmetric auctions. Together, these figures suggest a pattern: once firms have undergone LINC training, they appear to behave more aggressively (1a); ineligible firms (constituting the majority of the state's bidding firms), behave more aggressively when facing LINC-trained rivals (1b) than when facing untrained firms; ineligible firms' bids appear no different when they face only peer ineligible firms compared to when a LINC-trained rival participates (1c), but if the rival is untrained, behavior is less aggressive (1d). We investigate this story rigorously in our empirical work by modeling firms' decisions and accounting for many other factors that are not accounted for in these motivating figures.[5]

We continue our investigation of the effects of the LINC program by describing our data and determining what might drive qualified firms to participate in LINC. Note that, we take as given, the set of eligible firms—these, by requirement of the LINC program, must be firms that have been certified as a DBE, HUB, or SBE for at least one year.[6]

[5]Kolmogorov–Smirnov tests suggest that the empirical distributions are significantly different at the one-percent level in subplots 1b and 1d; the distributions in subplot 1a are significantly different at the ten-percent level (while visually a difference appears, the underlying sample sizes are smaller than in the other subplots); we fail to reject a null that the distributions are the same in subplot 1c, perhaps not surprisingly as the two nearly overlap each other.

[6]There seems to be little downside, and perhaps only benefits, to claiming such DBE/HUB/SBE status. Anecdotal evidence of this might be Representative Tammy Duckworth's (D, Illinois) "questioning" during a House Oversight and Government Reform Committee hearing of federal contractor Braulio Castillo who was accused of exploiting the system of veterans benefits. During her questioning Rep. Duckworth revealed that "Iraq and Afghanistan veterans right now are waiting an average of 237 days for an initial disability rating..."

2.1 Data Description

In our analysis, we use data from regularly-scheduled TxDOT highway procurement auctions conducted between September 1997 and August 2007. Data from September 1997 to August 1998 are used to create bidder-specific histories such as a measure of workload commitment (commonly referred to in the auctions literature as backlog). Thus, our empirical analysis in what follows employs the data from September 1998 through August 2007. Prior to bidding, all bidders learn the location and the detailed project description, the estimated number of days to complete the project, the engineer's estimate of the cost of executing the project, and the list of contractors who purchased the documents providing the initial plan description (the plan holders). Projects are awarded using the low-price, sealed-bid (procurement) auction format. The bidding process opens a minimum of 28 days after the plan for a project is posted. When the bidding period expires, the offers submitted by each bidder are revealed and the winner is announced. The winning bidder is determined solely by price—the lowest bidder is awarded the right to complete the respective task for the government. For each contract, we observe the identities of the firms that requested plans, the identities of all firms that tendered a bid along with the amount of each bid, as well as the engineer's cost estimate, projected time to complete the contract, and details concerning the tasks each contract requires. We complement these data with firm-specific LINC-eligibility and LINC-participation data and we construct, using each firm's past bidding behavior, other variables that might be important in driving observed behavior.

In Table 1, we present sample summary statistics for the full sample, for ineligible/non-qualified (non-LINC) firms, and for LINC-eligible firms. We partition the LINC-eligible firms into two groups: untrained and trained. The untrained firms include firms that are eligible but choose not to participate in the program and those who eventually get trained, but are observed in our data before training. In the full sample, we find 1749 unique firms holding plans. Of those firms, 229 are LINC-qualified prime bidders, 90 of which have participated in the LINC program.[7] In our sample period, 58 LINC

[7]We remind readers that 229 is not equal to the number of untrained plus the number of trained bidders because some firms classify as untrained in part of our sample, then they complete LINC training and afterwards are classified as trained. Moreover, some use LINC training as an opportunity to enter the industry as a prime contractor and so we see activity only as a LINC-trained firm. Thus, 229 is the number of unique LINC-eligible firms.

Table 1: Summary statistics

	Bidder category			
			LINC qualified	
Variable	All	Non-LINC	Untrained	Trained
Number of plan holder firms	1749	1520	198	90
Number of plans held	53683	47290	3101	3292
Number of bidding firms	1057	924	124	58
Number of bids	31783	28480	1564	1739
Number of winning firms	655	564	83	44
Number of wins	7434	6613	406	415
Bidding-to-plan holder ratio	.587	.596	.492	.549
	(.229)	(.225)	(.271)	(.208)
Relative bid	1.086	1.084	1.110	1.087
	(.243)	(.242)	(.256)	(.258)
Relative winning bid	.977	.977	.976	.968
	(.178)	(.178)	(.179)	(.174)
Engineer's estimate (in millions of $)	4.072	4.269	2.758	2.195
	(11.4)	(11.8)	(7.740)	(8.498)
Number of days to complete the project	153.219	155.232	132.880	140.782
	(172.422)	(176.462)	(128.438)	(139.664)
Complexity of the project (bid components)	64.824	65.135	61.577	63.017
	(61.329)	(62.163)	(52.199)	(47.090)

Standard deviations are in parentheses.

participants went on to eventually submit bids (constituting 1739 bids) and we observe 44 of them winning at least one contract. The bidding-to-plan holder ratio is a measure of bidding frequency of those indicating interest in a project by purchasing a plan. When considering this ratio, participation rates for ineligible firms are about ten percent higher than those for LINC-qualified, but untrained firms. LINC training cuts this disparity in half. Note too, that if the number of wins is normalized by the number of bids, the winning-to-bidding ratio is fairly consistent across the categories. A potentially important difference is that the number of LINC-trained firms submitting these winning bids is just over half that of the number of untrained winners, indicating that training might improve success rates of a given firm.

The table suggests some potential for government savings. Before training, LINC-qualified firms submit relative bids that are about two percent higher than traditional firms, though this difference goes away after LINC training. We also see that after training, LINC bidders' relative winning bids are about one percent lower than those of other groups. The last three rows of the table indicate the type of contracts in which bidding occurs may play an important role. These variables proxy for the average size or complexity of the projects on which bids are submitted. LINC-qualified bidders, on average, bid on projects that are estimated by state engineers to cost about $1.5 million less than projects non-LINC firms bid on (and this difference increases after training). We also see that projects undertaken by qualified bidders take 15–20 days less, on average, than those by ineligible bidders. Qualified bidders also undertake projects that are typically less complex in that they have fewer components. Taken together, the table suggests potentially important changes to bidder behavior, perhaps from LINC participation. We will account for these in our empirical work that follows to understand the effects of this program.

2.2 LINC Participation

Before considering the effects of LINC training, we first consider what might drive eligible firms to participate in the program. Specifically, we consider a probit model using monthly data to explain the probability of participating. The first time a LINC-eligible firm requests plans, the firm is assigned a response variable taking a value of zero (having not participated in LINC). If the firm completes the LINC program, the response variable changes to a one and then the firm is dropped from the panel. We restrict attention to LINC-qualified entrants since 2001, the inception year of the LINC program as firms that entered earlier did not have the opportunity to participate, even if they would have been willing to. We also only consider months in which qualified firms had the opportunity to participate in LINC.

In Table 2, we present the estimates of three probit regressions as marginal effects. The models differ by various measures of a given firm's experience which is captured by the past winning-to-bidding, winning-to-plan holder, and bidding-to-plan holder ratios. Typically, the more experienced the LINC-eligible firm, the less likely the firm is to participate in LINC. For example, model (1) suggests that a one-unit increase in a firm's winning-to-bidding ratio means the firm is 3.4% less likely to participate in the LINC training program. The lower experience effects are more salient for firms that have won often in the past compared to those that have garnered experience primarily through simply participating (bidding) in auctions as the past bidding-to-plan holder ratio is negative but not significant in model (3).[8]

Table 2: LINC Training Participation Decision

	Probability of participation in LINC		
Variable	(1)	(2)	(3)
Past winning-to-bidding ratio	-0.034***		
	(0.009)		
Past winning-to-plan holder ratio		-0.053***	
		(0.013)	
Past bidding-to-plan holder ratio			-0.016
			(0.012)
Log (maximum backlog + 1)	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
Log (total number of rivals faced in the market + 1)	0.025***	0.025***	0.025***
	(0.003)	(0.003)	(0.003)
Log (total number of LINC rivals faced in the market + 1)	-0.011	-0.012	-0.011
	(0.007)	(0.007)	(0.007)
Unemployment rate	-0.004	-0.004	-0.003
	(0.004)	(0.004)	(0.004)
Three month average of the real volume of projects	0.001	0.001	0.002
	(0.011)	(0.011)	(0.010)
Number of observations	1,538	1,538	1,538
Pseudo R^2	0.548	0.548	0.553
Wald χ^2	233.760	234.970	218.210

Robust standard errors are given below point estimates in parentheses and *** denotes statistical significance at the 1% level.

In all models, we include a set of controls to capture economic conditions facing a firm, characterizing the market, or expected to obtain in the future. The maximum backlog and number of rivals faced are firm-specific—the maximum backlog capturing the size (capacity) of the firm and the number of rivals being the number of unique plan holders a firm has faced in its previous participation in auctions. If the firm has existing projects it is slightly less likely to participate. This finding is

[8] A model with all three of the ratios is not included given that, by definition, the three are functions of each other. For example, the winning-to-plan holder ratio equals the winning-to-bidding ratio times the bidding-to-plan holder ratio.

statistically significant and robust across specifications. The magnitude of this effect is much lower than the effects from increased competition. Firms that faced a larger number of rivals in the past are more likely to participate in the program. The monthly unemployment rate in Texas is included as a control, though it is not significant nor is the average value of potential projects which is computed as a three-month moving average value of projects offered by TxDOT. Having considered what might determine a firm's participation decision, we now consider the effects of LINC training.

3 The Effects of LINC Training

While the summary statistics in Table 1 suggest some interesting patterns, they provide little direct evidence of how entry, bidding, and winning may have been affected by the LINC program as we saw the types of contracts firms chose to bid on were different across the categories of firms. The firm characteristics driving LINC participation suggest important controls that must be accounted for in going forward—namely a bidder's experience, backlog, and the competitiveness of an auction. In this section, we attempt to control for factors that may be varying across the sample periods, auctions, and bidders in order to better gauge the effects the LINC program has had on this market. We partition our analysis into two types of results: the first concerns probabilities of actually bidding and winning while the second concerns the levels of bids and winning bids.

3.1 Likelihood of Bidding and Winning

First, we examine whether participation in the LINC program affected the entry patterns for LINC-qualified bidders. To consider this, we estimated probit models characterizing the probability of bidding in a given auction, conditional on the firm holding plans, and present estimation results in columns (1) and (2) of Table 3.[9] Our main interest is in the coefficient of the dummy variable "LINC-trained firm" which takes a value of one if the firm is a LINC-qualified firm *and* has completed the training program and takes a value of zero otherwise. Note that "LINC-qualified, but untrained firm" is also

[9] One might imagine a precursor to this analysis considering whether LINC training affects the probability of requesting plans. We do not present such analysis in large part because plans are of minimal cost and when comparing the likelihood of requesting plans before-and-after training, we found no important effects. As simple evidence, a t-test considering whether the average number of proposals requested per month before LINC training is the same as that of after training (considering only firms that eventually train) is rejected at conventional levels and has a p-value of 0.29.

a dummy variable that takes a value of one if the bidder is in fact a LINC-qualified firm, but instead indicates that the firm has not participated in the training program, and is zero otherwise. Again, this may involve firms that were invited but chose not to participate in the program and firms that eventually participated in LINC, but we observe them in our data before they participated. While these variables capture average differences in the participation and success between LINC-eligible and ineligible firms, as well as allow us to understand the direct effect of the LINC training program, we are also interested in any indirect effects that might result. As such, we include a dummy variable "Interest from LINC-trained firm" to capture how the behavior of rival firms might change when a LINC-trained firm shows interest in a project. This takes a value of one when a LINC-trained firm holds plans for a given auction and measures the indirect effect of the LINC program.[10] We consider our full (September 1998 to August 2007) sample in models (1) and (2) and restrict attention to only the LINC-qualified sample in model (3).

Most of our other independent variables serve as a set of controls and involve accounting for things that are commonly used in the auctions literature. They can be categorized as representing auction, firm-specific, rival, and market characteristics. As project characteristics, we include the estimated cost of the project provided by state engineers, the number of potential rivals (plan holders), the days to complete a project, the complexity of a project as measured by the number of bid components, the project's materials shares, and the project division identified by TxDOT. The firm-specific characteristics involve the share of the firm's capacity utilized, the logarithm of the firm's distance to the project location, a dummy variable that takes the value of one if the firm has an ongoing project in the same county as the current project county, and the number of past bids. Proximity and concurrent involvement in local projects can reduce moving costs and create the opportunity to share resources more effectively across projects. The number of past bids is used to capture any experience gathered from prior bidding. As rival characteristics, we include the average rivals' past winning-to-plan holder

[10]To be explicit, consider an auction in which the plan holders are one LINC-trained firm, one LINC-qualified, but untrained firm, and three firms ineligible for the program. The dummy variable takes a value of one for all but the LINC-trained plan holder, in which case it takes a value of zero. If the same situation arose but there were two LINC-trained plan holders at the auction, the variable would take a value of one for all bidders at auction given everyone has at least one LINC-trained potential rival. Of course, if no LINC-trained firms request plans for a given auction, the variable takes a value of zero for all firms in that auction.

ratio, rivals' minimum backlog, and the logarithm of the closest rival's distance to the project location. Finally we include a set of time dummies to control for market fluctuations. A detailed description of these variables is provided in the Appendix.

Table 3: Results for Probability of Entry and Winning Conditional upon Entry

Variable	Pr[Entry|Plan holder]			Pr[Winning|Entry]		
	Full sample		LINC-qualified	Full sample		LINC-qualified
	(1)	(2)	(3)	(4)	(5)	(6)
LINC-qualified, but untrained firm (β_1)	-0.096***	-0.050***		0.027**	0.013	
	(0.010)	(0.010)		(0.012)	(0.012)	
LINC-trained firm (β_2)	-0.048***	-0.049***	-0.033*	0.019*	0.013	0.024
	(0.009)	(0.009)	(0.019)	(0.011)	(0.011)	(0.023)
Interest from LINC-trained firm	0.024***	0.019***	0.022	-0.007	-0.005	-0.027
	(0.005)	(0.005)	(0.017)	(0.006)	(0.006)	(0.019)
Log of engineer's estimate	0.008**	0.009***	0.006	-0.002	0.004	-0.030***
	(0.003)	(0.003)	(0.010)	(0.004)	(0.004)	(0.012)
Log number of plan holders	-0.185***	-0.151***	-0.133***	-0.199***	-0.204***	-0.162***
	(0.007)	(0.008)	(0.025)	(0.008)	(0.008)	(0.028)
Log number of days to complete the project	0.002	0.004	-0.022	-0.001	-0.001	0.013
	(0.004)	(0.004)	(0.014)	(0.005)	(0.005)	(0.016)
Log complexity	-0.013***	-0.040***	-0.052***	0.004	0.001	0.038***
	(0.004)	(0.004)	(0.013)	(0.005)	(0.005)	(0.014)
Bidder's capacity utilized		0.020**	-0.024		-0.074***	-0.129***
		(0.010)	(0.033)		(0.011)	(0.037)
Log of bidder's distance to the project location		-0.045***	-0.049***		-0.021***	-0.016**
		(0.002)	(0.007)		(0.002)	(0.007)
Ongoing project in the same county		0.136***	0.166***		0.078***	0.058***
		(0.006)	(0.019)		(0.006)	(0.022)
Log number of past bids		0.040***	0.071***		-0.007***	-0.015*
		(0.001)	(0.006)		(0.002)	(0.008)
Average rivals' winning-to-plan holder ratio		-0.336***	-0.525***		-0.539***	-0.514***
		(0.050)	(0.161)		(0.052)	(0.174)
Log of rivals' minimum backlog		-0.003***	-0.005***		-0.001***	-0.003*
		(0.000)	(0.001)		(0.000)	(0.001)
Log of closest rival's distance to the project location		0.026***	0.030***		0.020***	0.001
		(0.002)	(0.008)		(0.003)	(0.009)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Material shares	Yes	Yes	Yes	Yes	Yes	Yes
Project division effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	53,683	53,683	6,393	31,783	31,783	3,303
Pseudo R^2	0.049	0.094	0.120	0.035	0.051	0.082
Wald χ^2	2,660.680	5,426.230	889.010	1638.440	1,639.440	289.090
χ^2 test probability: $\beta_1 = \beta_2$	0.002	0.931		0.608	0.986	

Robust standard errors are given below point estimates in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

The results indicate that LINC-eligible firms, relative to the ineligible firms (our omitted group) are 4.8–9.6% less likely to bid in a given auction. The results in model (1) include only project-specific features of the contract and suggest LINC training increases a plan holder's probability of entry. However, when firm-specific and rival-specific characteristics are controlled for, the difference disappears: using the estimates in columns (1) and (2), we test whether $H_0 : \beta_1 = \beta_2$ against a two-sided alternative and our results change dramatically as we fail to reject the null once the other controls are added; however, when we restrict attention to the LINC-qualified sample in column (3), the training dummy variable is significantly different from zero at the 10% level. The estimates indicate that as the number of plan holders, project complexity, and a bidder's distance to project location increases, or when they are facing strong rivals, a firm's probability of entering an auction decreases. Bidders who have ongoing projects in the same bidding location (same county), those facing rivals who are located farther away from a project site, or those who have bidding experience have a higher probability of entry.

In models (4)–(6) of Table 3, we consider whether the probability of winning conditional on bidding at an auction changes after a firm has graduated from the LINC program. Our results indicate that once bidder- and rival-specific effects are controlled for, neither being LINC-qualified nor being LINC-trained affects the chances of winning at auction. Bidders with higher capacity utilized, those located farther from the project location, and those facing competitive rivals are less likely to win, while those firms having ongoing projects in the same county appear more likely to win. Interestingly, experience seems to work against the chances of winning for firms but this could be because experience tempers firms from bidding too aggressively. Of course, the bidding behavior of firms and the question of whether bidding has changed is driving the relationship between these two sets of empirical results—something we explore further in the next subsection.

3.2 Bidding and Winning Bids

We examine next whether bidding has been affected by the LINC training program. In Table 4 we provide a set of least squares regression results for the full sample and the restricted sample of LINC-qualified bidders. Specifically, in the first four columns we consider explaining variation in the logarithm of all tendered bids while in the last four columns we restrict attention to the log of only winning bids.

Table 4: Bid Regression Results

Variable	Log of bids				Log of winning bids			
	Full sample		LINC qualified		Full sample		LINC qualified	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LINC-qualified, but untrained firm (β_1)	-0.005	0.002			-0.013	-0.008		
	(0.005)	(0.005)			(0.009)	(0.009)		
LINC-trained firm (β_2)	-0.021***	-0.017***	-0.029***	-0.045***	-0.031***	-0.026***	-0.022	-0.034
	(0.005)	(0.005)	(0.010)	(0.015)	(0.008)	(0.008)	(0.018)	(0.027)
Interest from LINC-trained firm	-0.017***	-0.016***	0.005	-0.006	-0.015***	-0.014***	-0.009	-0.027
	(0.004)	(0.004)	(0.010)	(0.010)	(0.005)	(0.005)	(0.016)	(0.017)
Log of engineer's estimate	0.935***	0.931***	0.940***	0.924***	0.945***	0.943***	0.946***	0.933***
	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.003)	(0.010)	(0.010)
Log number of plan holders	-0.017***	-0.019***	-0.023*	-0.013	-0.069***	-0.071***	-0.116***	-0.078***
	(0.006)	(0.006)	(0.014)	(0.014)	(0.006)	(0.006)	(0.021)	(0.021)
Log number of days to complete the project	0.034***	0.034***	0.030***	0.026***	0.026***	0.026***	-0.001	0.005
	(0.004)	(0.004)	(0.008)	(0.008)	(0.004)	(0.004)	(0.014)	(0.015)
Log complexity	0.068***	0.073***	0.055***	0.068***	0.087***	0.091***	0.095***	0.101***
	(0.005)	(0.005)	(0.008)	(0.009)	(0.005)	(0.005)	(0.013)	(0.013)
Bidder's capacity utilized		0.030***	0.026	0.040**		0.014*	0.021	0.054*
		(0.005)	(0.016)	(0.017)		(0.008)	(0.026)	(0.031)
Log of bidder's distance to the project location		0.015***	0.010***	0.014***		0.006***	0.006	-0.002
		(0.001)	(0.003)	(0.005)		(0.002)	(0.006)	(0.010)
Ongoing project in the same county		-0.023***	-0.031***	-0.010		-0.017***	-0.029*	-0.024
		(0.003)	(0.009)	(0.009)		(0.004)	(0.015)	(0.015)
Log number of past bids		0.003***	0.004	-0.003		0.004***	0.002	-0.014
		(0.001)	(0.004)	(0.007)		(0.002)	(0.006)	(0.014)
Average rivals' winning-to-plan holder ratio		-0.063*	-0.001	-0.084		-0.203***	-0.135	-0.074
		(0.035)	(0.100)	(0.096)		(0.039)	(0.137)	(0.143)
Log of rivals' minimum backlog		0.001***	0.000	-0.000		0.001*	-0.001	-0.001
		(0.000)	(0.001)	(0.001)		(0.000)	(0.001)	(0.001)
Log of closest rival's distance to the project location		-0.001	0.007*	0.005		0.004**	0.012*	0.011
		(0.002)	(0.004)	(0.004)		(0.002)	(0.006)	(0.007)
Firm effects	No	No	No	Yes	No	No	No	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Material shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Project division effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	31,783	31,783	3,303	3,278	7,434	7,434	821	816
R^2	0.984	0.984	0.983	0.985	0.989	0.989	0.991	0.994

** denotes statistical significance at the 5% level. * denotes statistical significance at the 10% level.
Clustered (by auction) robust standard errors are in parentheses.

When all firms are considered, as in models (1) and (2), the omitted group is the ineligible/non-LINC firms.[11] There is no statistically significant difference in the bidding behavior of LINC-qualified, but untrained firms and the ineligible firms. However, the estimate of the coefficient β_2 indicates that after completing LINC training, firms bid more aggressively compared to their pre-LINC-training levels and relative to the ineligible firms. Specifically, LINC-trained firms bid 1.7% lower than other vying firms. Perhaps as important is the indirect competition effect which here captures the bidding behavior of firms that submit offers on projects which LINC-trained firms expressed interest in. When that is the case, the bid is 1.6% lower on average. We have some confidence in this indirect competition effect as we considered other models in which we included placebo-like effects.[12] For example, if we include a variable capturing whether plans for the auction were held by a LINC-qualified, but untrained firm (either along with or instead of the one representing our indirect competition effect) it is never statistically different from zero and is always smaller in magnitude, being at most 0.004 away from zero. In short, on average, the training program seems to be generating aggressive bidding both directly from the program's graduates, and indirectly through more competitive behavior from rival firms when LINC graduates hold plans for an auction.

The other coefficient estimates suggest patterns that are intuitively appealing. If there are more plan holders at auction, if a firm has another project going on in the same county and can, perhaps, generate synergistic benefits, or if the rivals have been more successful in past auctions, then lower bids are tendered. If the size, length, or complexity of the project is larger/higher, then higher bids are submitted. Likewise, higher bids obtain when bidders have used much of their capacity or if firms are farther from the project location. All of these effects are statistically significant at the 1% level even after controlling for time, project composition, and project division effects. While statistically significant, a bidder's experience and the rivals' minimum backlog are both very small in magnitude. Their signs indicate that having tendered many bids in the past or facing rivals with many ongoing projects led a firm to tender higher bids on average.

[11] We do not discuss extensively model (1) here, but present it to help give a baseline and to frame a bid homogenization procedure that we will later use.

[12] Space constraints prevent us from presenting everything here, but these results are available from the authors if readers are interested.

In columns (3) and (4) of Table 4 we restrict attention to the subsample of bids generated by LINC-qualified firms. As such, the omitted group now becomes the set of firms that opt not to undergo training. Relative to this group of untrained, but eligible firms, LINC bidding is even more competitive—the results suggesting bids that are 2.9% or 4.5% lower, depending on whether firm fixed effects are accounted for as in column (4).[13] Moreover, driving identification of β_2 is simply the change realized by bidders who at some point in our data chose to undergo LINC training. The magnitude of the coefficient is larger in absolute value suggesting bids from these firms dropped by 4.5% on average after training. In both models, the indirect competition effect is no longer significant. The estimated coefficients of the other covariates included and discussed above are, for the most part, consistent with their respective counterparts in model (2), though significance is harder to achieve in this restricted sample.

Finally, in the last four columns of Table 4, we maintain the same structure of the four empirical models discussed but restrict attention to the subset of winning bids. With respect to the full sample of winning bids, being LINC-qualified alone does not suggest differences in bidding behavior relative to ineligible firms as the estimate of β_1 is not significant, but again LINC training seems to make a difference. LINC-trained firms generate bids that are, on average, 2.6% lower than that of their rivals. Moreover, the average rivals' winning bid is 1.4% lower when a LINC graduate is interested in a project. In column (6), the results indicate that the sign and significance of the other covariates are similar to those of the full sample of bids presented in model (2), though the magnitude of some estimates has changed. When we consider only winning bids from LINC-qualified firms as in columns (7) and (8), statistical significance is lost for most covariates and, in particular, for the LINC-related coefficients of interest, though we will revisit this later.

The group of subplots we presented in Figure 1 suggested that the effects on bidding behavior may hold not only on average, but might be important throughout the bid distribution. As such, in Table 5, we complement the bid regressions presented above by providing a portion of some quantile bid

[13] Since firm fixed effects are used in (4), we include only bidders that are observed multiple times in the sample in order to identify the firm-specific fixed effects. Therefore, we have dropped 25 observations from one-time bidders.

Table 5: Quantile Bid Regression Results

	Log of bids								
Variable	q10	q20	q30	q40	q50	q60	q70	q80	q90
LINC-qualified, but untrained firm (β_1)	-0.005	0.001	-0.001	-0.004	-0.002	-0.008	-0.001	0.002	0.020
	(0.006)	(0.006)	(0.005)	(0.007)	(0.006)	(0.009)	(0.008)	(0.009)	(0.015)
LINC-trained firm (β_2)	-0.034***	-0.022***	-0.024***	-0.019***	-0.019***	-0.019***	-0.013**	-0.010	-0.008
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Interest from LINC-trained firm	-0.017***	-0.011***	-0.014***	-0.018***	-0.018***	-0.020***	-0.020***	-0.023***	-0.020***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)
Number of observations					31,783				

	Log of winning bids								
	q10	q20	q30	q40	q50	q60	q70	q80	q90
LINC-qualified, but untrained firm (β_1)	-0.003	-0.007	-0.004	-0.011	-0.018**	-0.019**	-0.024***	-0.024**	-0.014
	(0.022)	(0.014)	(0.010)	(0.010)	(0.008)	(0.008)	(0.009)	(0.012)	(0.016)
LINC-trained firm (β_2)	-0.023*	-0.040***	-0.030**	-0.026**	-0.031***	-0.028***	-0.024**	-0.009	-0.019
	(0.012)	(0.014)	(0.013)	(0.010)	(0.008)	(0.009)	(0.010)	(0.011)	(0.014)
Interest from a LINC-trained firm	-0.010	-0.015***	-0.010**	-0.015***	-0.018***	-0.020***	-0.018***	-0.015**	-0.015*
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)
Number of observations					7,434				

Bootstrapped standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

These regressions are specified exactly as the models estimated in the columns labeled (2) and (6) of Table 4, but we only present estimates of these coefficients given our interest and due to space constraints.

regression results for the models estimated in the columns labeled (2) and (6) of Table 4. We limit presentation to these two models as conveying estimates at each decile requires more space. As such, we also limit our presentation to the estimates of our primary coefficients of interest (those corresponding to the LINC-related variables in the top three rows of our bid regression table). Nonetheless, the models estimated are specified exactly as they were in columns (2) and (6) of Table 4 in the sense that all of the other covariates and fixed effects were included in the estimation. Table 5 has two parts: the top set of estimates concerns the log of all bids as the response variable, while the bottom relate to the log of only winning bids. The results discussed above concerning the bidding behavior of LINC-qualified firms hold throughout much of the distribution. If a firm is LINC-qualified, but untrained, its bidding behavior is never statistically different from the ineligible firms; however, LINC-trained firms behave more aggressively by submitting bids that are 1.3–3.4% lower than the other firms throughout the first seven deciles of all tendered bids. The indirect competition effect is statistically significant for every quantile presented. The magnitude of these coefficients is also consistent with the least-squares estimate. The results concerning winning bids also appear to hold not just at the mean bid, but throughout much of the distribution. Unlike the least-squares regressions, the winning bids from LINC-qualified, but untrained firms are statistically different from (lower than) ineligible-firm winning bids for the median through the 80th percentile. As such, there is some resemblance in the winning bids from untrained and trained firms for this part of the winning bid distribution. Still, winning bids from LINC-trained firms are significantly lower than those from ineligible firms for seven of the nine deciles and the indirect competition effect is significant for all but the lowest decile of the winning bid distribution.

One may also wonder whether LINC training (or the qualification of LINC-eligibility) might be affecting bidding behavior through other important channels. For example, the results in Table 4 suggest that many covariates, as we discussed above, might be important in driving the bidding decisions of firms. Backlog or capacity constraints as well as distance to a project location and strength of the competition have all been salient issues in important empirical papers concerning auctions; as examples, see Bajari and Ye [2003], Jofre-Bonet and Pesendorfer [2000, 2003], De Silva et al. [2003], De

Table 6: Investigating other Possible Asymmetries through Bid Regressions

Variable	Log of bids			Log of winning bids		
	(1)	(2)	(3)	(4)	(5)	(6)
LINC-qualified, but untrained firm (β_1)	-0.001	0.025	0.021	-0.013	0.028	0.008
	(0.007)	(0.017)	(0.016)	(0.012)	(0.028)	(0.025)
LINC-trained firm (β_2)	-0.016**	-0.033**	-0.046**	-0.039***	-0.038	-0.056**
	(0.007)	(0.015)	(0.019)	(0.012)	(0.025)	(0.024)
Interest from LINC-trained firm	-0.016***	-0.016***	-0.016***	-0.014***	-0.014***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Bidder's capacity utilized	0.030***	0.030***	0.030***	0.010	0.014*	0.014*
	(0.005)	(0.005)	(0.005)	(0.009)	(0.008)	(0.008)
Bidder's capacity utilized ×	0.019			0.029		
LINC-qualified, but untrained firm (β_1)	(0.021)			(0.032)		
Bidder's capacity utilized ×	-0.006			0.063*		
LINC-trained firm (β_2)	(0.020)			(0.037)		
Log of bidder's distance to the project location	0.015***	0.015***	0.015***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Log of bidder's distance to the project location ×		-0.006			-0.009	
LINC-qualified, but untrained firm (β_1)		(0.004)			(0.007)	
Log of bidder's distance to the project location ×		0.004			0.003	
LINC-trained firm (β_2)		(0.003)			(0.006)	
Average rivals' winning-to-plan holder ratio	-0.063*	-0.063*	-0.064*	-0.204***	-0.202***	-0.205***
	(0.035)	(0.035)	(0.035)	(0.039)	(0.039)	(0.040)
Average rivals' winning-to-plan holder ratio ×			-0.132			-0.109
LINC-qualified, but untrained firm (β_1)			(0.101)			(0.162)
Average rivals' winning-to-plan holder ratio ×			0.205			0.221
LINC-trained firm (β_2)			(0.132)			(0.157)
Material shares	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Project division effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	31,783	31,783	31,783	7,434	7,434	7,434
R^2	0.984	0.984	0.984	0.989	0.989	0.989

Clustered (by auction) robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

These regressions expand the models presented in the columns labeled (2) and (6) of Table 4 by adding interaction terms.

Silva et al. [2008], as well as Bajari et al. [2014]. We explore these possible channels as ways in which firms might behave differently given their classification by considering other regression models in Table 6. The table is again partitioned by all bids (the first three columns of estimates) and winning bids (the last three columns). All of the models estimated include all covariates presented in the columns labeled (2) and (6) of Table 4 but, due to space constraints we only present coefficient estimates for our variables of interest and the relevant terms for the newly-considered cases. First, note that the significance of the LINC-trained dummy variable holds in all expanded models except for the case of winning bids when we consider asymmetric responses to distance (though the magnitude of the effect is larger than the results from Table 4, the p-value is 0.13). Second, the results concerning the indirect competition effect are consistent with our earlier discussions for all models.

The estimates in columns (1) and (4) of Table 6 consider interactions between the bidder's capacity utilized and its LINC status. In short, firms eligible for the LINC program who are untrained behave no differently when it comes to capacity utilized than ineligible firms. Once a firm undergoes LINC training, behavior on average does not change but there is some evidence (significant at the 10% level) that LINC-trained winners react to their capacity utilized in a statistically different way from ineligible firms (though not from LINC-qualified, but untrained firms). In columns (2) and (5), we consider whether the bids of LINC-qualified firms might be different from ineligible firms based on how close the firm is to the project site. Again, there is no difference on average in the behavior of qualified firms compared to ineligible firms, and this does not change once the firm completes LINC training. Lastly, in columns (3) and (6), we investigate whether these firms might respond differently to the perceived competitiveness of their rival firms. We consider interactions between our LINC-qualified dummy variables with the average of their rivals' winning-to-plan holder ratio. The interactions are never significant—suggesting response to rivals' success, though important on average, does not differ from ineligible firms, whether the LINC-qualified firm is trained or not. These potential explanations involved asymmetries that could be considered using our observed data. Since there was little evidence to support them, we consider an alternative later by constructing a structural approach. It is built on the idea that perhaps the LINC-trained firms bid differently because the program affected something we cannot observe directly in the data, such as the firms' cost structure.

A concern one might have with the bid regressions presented thus far is selection bias. As shown above (Table 2), the decision to participate in LINC is non-random. Moreover, being LINC-qualified seems to affect entry behavior at auctions (Table 3). If LINC training is allowing firms to identify contracts that are most appropriate once the plans are held, then the bids observed are non-random. For example, we as econometricians do not see bids from LINC-trained firms on contracts that they decided were not worth their time pursuing. We address these concerns using two Heckman-based corrections. First, we estimate the probability of participating in the LINC training program by using propensity scores derived from the probit models presented in Table 2. This score will be zero for LINC-ineligible firms, one for LINC-trained firms, and somewhere between zero and one for LINC-qualified, but untrained firms.[14] This score variable introduces a new variable that we have not included in our bid regressions, but that will be related to whether a bid is submitted on a contract given a firm holds plans.[15] We use this propensity score along with auction-specific covariates to estimate the probability of a given firm tendering a bid at a certain auction. This constitutes our selection approach, which is then used in the second-stage bid regressions after evaluating the inverse-Mills ratio at the respective covariate vector.

We replicate the models presented in Table 4 following the sample selection procedure discussed and present corresponding estimates in Table 7. The coefficient on the inverse-Mills ratio is statistically different from zero in three of the models, all involving winning bids, suggesting sample selectivity is not overwhelming our estimates.[16] Comparing the results here to those presented in Table 4 shows two things: first, the coefficients of the majority of the covariates we included are largely unchanged; second, the primary coefficient of interest which measures the effect of LINC training strengthens—statistical significance of LINC training is achieved in all models now and the magnitude of this effect is larger in absolute value in nearly ever case. Lastly, the indirect competition effect continues to generate more aggressive bidding and more aggressive winning bids for nearly all the models.

Lastly, while our focus has been on the awarding of procurement contracts, readers may wonder whether post-winning behavior either differs across the classes of bidders or somehow cancels the savings generated at the awarding stage. Taking an extreme position, perhaps LINC graduates have somehow learned to submit skewed or deceptive bids for a project knowing that they will be able to renegotiate a higher payment after winning the contract. Such concerns were the basis of Bajari et al. [2014], in which the authors focused on the prevalence of renegotiation and post-awarding adaptation. To evaluate this, we obtained data on the final payments made to firms for contracts completed during

[14] Two related comments: first, since the LINC program began in 2001, the propensity score of every firm is zero before the inaugural training session; second, since LINC training is not available every month, we use the yearly average for months in which training was not available, which ensures the probability is updated throughout the sample.

[15] In models where we consider the log of winning bids, we use a propensity score derived from a probit in which the past winning-to-bidding ratio was used. We felt these were the natural results to present given they represent the underlying selection process we're trying to address.

[16] Although we do not present the results here, we also considered using a propensity score based off the past winning-to-bidding ratio, winning-to-plan holder ratio, or bidding-to-plan holder ratio for each model. The results are not presented here, available from the authors, and not distinguishable at the precision given in Table 7 in any way.

Table 7: Bid Regression Results with Heckman Approach

Variable	Log of bids				Log of winning bids			
	Full sample		LINC qualified		Full sample		LINC qualified	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LINC-qualified, but untrained firm (β_1)	-0.010	-0.002			-0.022**	-0.017*		
	(0.007)	(0.007)			(0.010)	(0.010)		
LINC-trained firm (β_2)	-0.024***	-0.020***	-0.026*	-0.042**	-0.036***	-0.032***	-0.036*	-0.045*
	(0.006)	(0.006)	(0.015)	(0.018)	(0.009)	(0.009)	(0.020)	(0.024)
Interest from LINC-trained firm	-0.015***	-0.015***	0.005	-0.006	-0.013**	-0.012**	0.004	-0.015
	(0.003)	(0.003)	(0.009)	(0.009)	(0.005)	(0.005)	(0.017)	(0.017)
Log of engineer's estimate	0.935***	0.931***	0.940***	0.924***	0.945***	0.943***	0.958***	0.944***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)	(0.003)	(0.012)	(0.012)
Log number of plan holders	-0.027**	-0.027**	-0.028	-0.019	-0.125***	-0.124***	-0.045	-0.017
	(0.011)	(0.011)	(0.023)	(0.022)	(0.025)	(0.025)	(0.047)	(0.044)
Log number of days to complete the project	0.034***	0.034***	0.029***	0.026***	0.026***	0.026***	-0.001	0.006
	(0.002)	(0.002)	(0.008)	(0.007)	(0.004)	(0.004)	(0.012)	(0.012)
Log complexity	0.067***	0.072***	0.054***	0.068***	0.086***	0.090***	0.088***	0.094***
	(0.002)	(0.002)	(0.007)	(0.007)	(0.004)	(0.004)	(0.013)	(0.013)
Bidder's capacity utilized		0.030***	0.027	0.040**		0.014	0.017	0.050*
		(0.005)	(0.016)	(0.017)		(0.008)	(0.028)	(0.027)
Log of bidder's distance to the project location		0.015***	0.010***	0.014***		0.006***	0.006	-0.002
		(0.001)	(0.003)	(0.005)		(0.002)	(0.005)	(0.007)
Ongoing project in the same county		-0.023***	-0.031***	-0.010		-0.017***	-0.027**	-0.023*
		(0.003)	(0.009)	(0.009)		(0.004)	(0.014)	(0.013)
Log number of past bids		-0.062***	-0.000	-0.084		-0.193***	-0.135	-0.077
		(0.022)	(0.080)	(0.080)		(0.036)	(0.121)	(0.117)
Average rivals' winning-to-plan holder ratio		0.003***	0.004	-0.003		0.004***	0.002	-0.015
		(0.001)	(0.004)	(0.007)		(0.001)	(0.005)	(0.011)
Log of rival's minimum backlog		0.001***	0.000	-0.000		0.001*	-0.001	-0.001
		(0.000)	(0.001)	(0.001)		(0.000)	(0.001)	(0.001)
Log of closest rival's distance to the project location		-0.001	0.007*	0.005		0.005**	0.013**	0.012**
		(0.001)	(0.004)	(0.004)		(0.002)	(0.006)	(0.006)
Inverse-Mills' ratio	0.040	0.033	0.028	0.029	0.083**	0.078**	-0161*	-0.143
	(0.041)	(0.041)	(0.103)	(0.097)	(0.035)	(0.036)	(0.095)	(0.090)
Firm effects	No	No	No	Yes	No	No	No	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Material shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Project division effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of uncensored observations	31,783	31,783	3,303	3,278	7,434	7,434	821	816

** denotes statistical significance at the 5% level. * denotes statistical significance at the 10% level.
Standard errors are in parentheses.

the years of our data sample.[17] In Table 8, we provide estimates from four models (two based on least-squares and two which address sample-selection concerns in the way we discussed above) in which our dependent variable is now the final payment made to the winning bidder, post any renegotiation and/or adjustments to the projects. The estimates in columns (1) and (3) condition on the engineer's initial estimate of the project while the estimates in columns (2) and (4) consider the winning bid. When the engineer's estimate is considered, the estimated coefficients for our direct and indirect LINC-related effects are nearly identical to those we obtained when the winning bid was used as a dependent variable. Thus, cost savings implied by the awarding stage are actually realized when the state writes its final check to the firm who completes the task. LINC-trained bidders are paid 3% less on average and the indirect competition effect generates savings of over 2%. When the winning bid is considered on the right-hand side, there is no significant effect of being a LINC-trained firm and no indirect competition effect. This is reassuring as it suggests that behavior in the post-awarding stage is unrelated to LINC-training and does not differ across our classes of bidders. Having considered this, we feel confident in saying that LINC graduates are not somehow manipulating the system in a way that wipes out any suggested savings the state receives from the auction. Moreover, renegotiation and/or adjustments needed after the contract has been awarded appear to be independent of which class bidders belong to.

In the introduction, we noted that operation of the LINC program costs the state about $200,000 per year. Using our estimates from model (6) of Table 4 (analogously, model (6) from Table 8 has nearly the same predictions) we can provide an estimate of the benefits the LINC program has generated. Specifically, we look in the data and identify which auctions were won by either (i) a LINC-trained firm for a project multiple LINC-trained firms were interested in, (ii) a LINC-trained firm in which the winning firm was the only LINC-trained firm that showed interest in the project, or (iii) a non-LINC-trained firm who won a contract that attracted the interest of a LINC-trained firm. We use the coefficient point estimates from the LINC-trained dummy and the indirect competition variable to

[17]We have data on final payments for completed contracts from September of 1999 until August of 2007, though many of the contracts started in the later part of our data sample were not finished when this information was provided.

Table 8: Bid Regression Results for Final Payments

Variable	Log of final pay (completed projects only)			
	OLS		Heckman	
	(1)	(2)	(3)	(4)
LINC-qualified, but untrained firm (β_1)	-0.003	-0.006	-0.007	-0.008
	(0.014)	(0.008)	(0.015)	(0.010)
LINC-trained firm (β_2)	-0.030**	0.002	-0.031**	0.001
	(0.012)	(0.008)	(0.012)	(0.008)
Interest from LINC-trained firm	-0.025***	-0.004	-0.023***	-0.003
	(0.007)	(0.005)	(0.007)	(0.005)
Log of engineer's estimate	0.935***		0.933***	
	(0.006)		(0.005)	
Log of winning bid		0.994***		0.993***
		(0.004)		(0.003)
Log number of plan holders	-0.077***	-0.014**	-0.104***	-0.029
	(0.010)	(0.006)	(0.033)	(0.021)
Log number of days to complete the project	0.045***	0.012**	0.045***	0.012***
	(0.008)	(0.005)	(0.007)	(0.004)
Log complexity	0.083***	-0.001	0.085***	0.000
	(0.008)	(0.006)	(0.007)	(0.004)
Bidder's capacity utilized	0.024*	0.005	0.024*	0.005
	(0.013)	(0.008)	(0.013)	(0.008)
Log of bidder's distance to the project location	0.000	-0.004*	0.000	-0.004**
	(0.003)	(0.002)	(0.003)	(0.002)
Ongoing project in the same county	-0.015**	0.002	-0.015**	0.002
	(0.007)	(0.004)	(0.007)	(0.004)
Log number of past bids	-0.200***	0.032	-0.196***	0.034
	(0.066)	(0.044)	(0.061)	(0.039)
Average rivals' winning-to-plan holder ratio	-0.000	-0.004**	-0.000	-0.004***
	(0.002)	(0.002)	(0.002)	(0.001)
Log of rivals' minimum backlog	0.001	-0.000	0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Log of closest rival's distance to the project location	0.000	-0.004**	0.001	-0.004**
	(0.003)	(0.002)	(0.003)	(0.002)
Selection				
LINC-qualified, but untrained firm (β_1)			-0.149***	-0.149***
			(0.055)	(0.055)
LINC-trained firm (β_2)			0.555	0.555
			(0.373)	(0.373)
Interest from LINC trained firm			0.078***	0.078***
			(0.024)	(0.024)
Log of engineering estimate			-0.064***	-0.064***
			(0.014)	(0.014)
Log number of plan holders			-1.013***	-1.013***
			(0.033)	(0.033)
Log number of days to complete the project			-0.002	-0.002
			(0.021)	(0.021)
Log complexity			0.062***	0.062***
			(0.019)	(0.019)
LINC participation probability – based on past winning-to-bidding ratio			-0.603	-0.603
			(0.371)	(0.371)
λ			0.039	0.021
			(0.045)	(0.029)
Time effects	Yes	Yes	Yes	Yes
Material shares	Yes	Yes	Yes	Yes
Project division effects	Yes	Yes	Yes	Yes
Number of uncensored observations	4,915	4,915	4,915	4,915

** denotes statistical significance at the 5% level. * denotes statistical significance at the 10% level. Standard errors are in parentheses.

recompute how much more expensive the auctions would have been had the respective firm not been LINC trained. Aggregating the savings across the three types of winning scenarios noted implies cost savings of over $21 million per year—this amounts to 1.49% of the total value of the engineer's estimates for these contracts and 1.55% of the total value of the actual winning bids for these contracts.[18] The negligible cost to TxDOT of running the LINC program pales in comparison to the funds saved and suggests large government savings. Another way to quantify the effect of the LINC program involves calculating the number of additional plan holders or bidders per auction that would be required to induce the same cost savings. Again, using the estimates from model (6) of Table 4 suggests that TxDOT would need to have, on average, an additional 0.95 plan holders or 0.56 bidders per auction to yield the same cost savings.

Our work here has measured the effects of LINC on participation, behavior, and success in TxDOT procurement contracting. However, the LINC program may imply changes to the cost structure of graduate firms. For example, perhaps their costs are improving which is allowing them to be more successful. In the same vein, it would be interesting to look at whether the efficiency of the procurement auctions has improved as a result of the LINC training program. Of course, analyzing bidding behavior is reasonably straightforward as bids are observed directly, but shedding light on these other issues involves understanding the (unobserved) cost structures of the firms. To investigate these questions involving firms' costs and the efficiency of the auctions, we construct a structural model of bidding behavior in the next section and present insight from estimating the latent cost distributions in the section that follows.

4 Structural Model of Bidding

In this section, we investigate further the change in observed bidding patterns by appealing to a theoretical model in which we allow for asymmetric bidders.[19] Note that we do not impose such an

[18]We compute a 95% confidence interval for these predictions by considering the coefficient estimates plus and minus the appropriate number of standard deviations and then re-predicting cost savings. Such an exercise puts the cost savings in the range of [$7.1 million, $41.7 million].

[19]While we remain agnostic as to the mechanism that might generate such an asymmetry, a number of stories are plausible for why this might be true. As an example, the networking aspect of LINC may allow prime contracts to coordinate and develop relationships with subcontractors. Such an understanding of the upstream subcontracting firms

asymmetry in our analysis, but rather, allow for the possibility in our estimation strategy which is nonparametric and, thus, data-driven. We organize this section as follows. In the first subsection, we describe the underlying model. In the second subsection, we discuss practical issues including the pooling of many types of heterogeneous auctions in which the composition of bidders differs in our empirical work.

4.1 Asymmetric Procurement Model

Consider TxDOT would like to complete an indivisible task at the lowest possible cost. Tenders are invited from n (≥ 2) bidders (firms) and are opened only once a submission deadline has passed. The contract is awarded to the lowest bidder, who wins the right to perform the task. TxDOT pays the winning firm its bid on completion of a contract. Assume that there is no price ceiling—a maximum acceptable bid that has been imposed by the buyer[20]

Assume bidders (firms) are risk neutral and belong to one of three classes.[21] Specifically, we refer to class 0 bidders as the ineligible/non-LINC bidders, to class 1 bidders as the LINC-eligible, but untrained bidders or the never trained bidders, and to class 2 bidders as the LINC graduates or the LINC-trained firms. Again, class 1 includes firms who are eligible and choose to never undergo LINC training and firms that eventually partake in the LINC program, but are observed before doing so.[22] Thus, a given firm may be a class 1 bidder in some auctions that took place early, chronologically speaking, and then, after completing the LINC program, be a class 2 bidder in later auctions. In such instances, the pre-training bids are considered to be from a class 1 bidder, while the post-graduation

means the prime contractor (bidder) can realize cost savings (or extract potential rents) by knowing when to use various suppliers who might specialize in a smaller subset of tasks. In addition, part of the training involves learning project-management techniques.

[20]This is reasonable as, in our data, such a value is never imposed nor is a contract ever not awarded due to bidding behavior, even though there are instances in which the winning bid for a contract exceeds an engineer's estimate of the cost to complete a given project. There are a small number of instances in which TxDOT cancels a project and then either redesigns it or combines it with other outstanding work.

[21]We are careful to refer to bidders as belonging to one of three *classes* and not as being of one of three *types* to prevent confusion with theoretical research concerning auctions. In that literature, a bidder of a certain type means a bidder having a specific cost value, regardless of which class she belongs to.

[22]We would love to consider an even finer partition by dividing up class 1 bidders but, given our estimation strategy will be nonparametric and the flexibility we are already allowing for by considering three classes of bidders, our data would be stretched far too thin to consider a distinction within this class as will be clear. Given curse-of-dimensionality issues, three classes of bidders already seems to be asking a lot of a given dataset—for example, two classes of bidders are considered by Campo et al. [2003], Flambard and Perrigne [2006], as well as Krasnokutskaya and Seim [2011].

bids belong to a class 2 bidder which is consistent with the analysis presented in Sections 2 and 3.

Let n_i denote the number of class i bidders at an auction where $n = n_0 + n_1 + n_2$. Suppose that each bidder of class i gets an independent cost draw from a distribution $F_i(c)$ which has an associated probability density function $f_i(c)$ that is strictly positive over the compact support $[\underline{c}, \overline{c}]$. The information set known to each firm includes $\{n_0, n_1, n_2, F_0(\cdot), F_1(\cdot), F_2(\cdot), \underline{c}, \overline{c}\}$ where we are explicit that the support of the cost distributions is the same for all classes of bidders. Note that each firm knows its cost draw but not the cost realizations of its rival firms; thus, since realized cost draws are privately known only to each individual firm, this is a game of incomplete information. This structure is what is known as the *asymmetric* independent private values paradigm (IPVP).[23]

Each firm i chooses its bid to maximize its expected profit

$$E[\pi_i(b_i)] = (b_i - c_i)\,\Pr(\text{win}|b_i).$$

Assuming each firm is using a class-specific bidding strategy $\beta_i(c_i)$ that is monotonically increasing in its cost, the probability a class i bidder wins the auction can be written

$$\Pr(\text{win}|b_i) = \left\{1 - F_i[\beta_i^{-1}(b_i)]\right\}^{n_i - 1} \prod_{j \neq i} \left\{1 - F_j[\beta_j^{-1}(b_i)]\right\}^{n_j}$$

where $\beta_i^{-1}(\cdot)$ is the inverse-bid function characterizing behavior of class i firms.

Substituting these expressions into the expected profit objective above and taking the first-order condition for profit maximization of each class of bidder yields a system of three differential equations, each of the form

$$(b_i - c_i)\left[\left(\frac{n_i - 1}{\beta_i'[\beta_i^{-1}(b_i)]}\right)\left(\frac{f_i[\beta_i^{-1}(b_i)]}{1 - F_i[\beta_i^{-1}(b_i)]}\right) + \prod_{j \neq i}\left(\frac{n_j}{\beta_j'[\beta_j^{-1}(b_i)]}\right)\left(\frac{f_j[\beta_j^{-1}(b_i)]}{1 - F_j[\beta_j^{-1}(b_i)]}\right)\right] = 1. \qquad (1)$$

These differential equations satisfy two boundary conditions: $\beta_i(\underline{c}) = \underline{b}$ and $\beta_i(\overline{c}) = \overline{c}$ for all $i = 1, 2, 3$ given firms have the same cost support. These conditions imply that the bidding strategies of both classes involve bidders of the highest possible type ($\overline{c}$) bidding truthfully and bidders of the lowest possible type ($\underline{c}$) tendering the same low bid in equilibrium. The system does not satisfy the Lipschitz

[23] Hickman et al. [2012] provided a guide to the structural econometric analysis of auction data which is organized by informational structure.

condition at the upper-end where a singularity obtains. Fortunately, existence and unqiueness of a monotone pure-strategy equilibrium (MPSE) has been shown by Lebrun [1999, 2006] as well as Maskin and Riley [2000a,b].

Another complication is that, while a unique solution exists, solving for it is often difficult; see, Hubbard and Paarsch [2014] for a summary of various approaches to solving asymmetric auctions. Fortunately, the empirical strategy we employ avoids the need to solve this system explicitly. Let $G_i(b)$ denote the equilibrium bid distribution of bids from class i which has corresponding density $g_i(b)$. In the seminal work of Guerre et al. [2000, GPV] the authors recognized that

$$G_i(b) = \Pr(B_i \le b) = \Pr[V_i \le \beta_i^{-1}(b)] = F_i[\beta_i^{-1}(b)] = F_i(v);$$

thus,

$$g_i(b) = \frac{f_i(v)}{\beta_i'(v)}.$$

Now, using the fact that $\beta_i^{-1}(b) = v$ and substituting these terms into the system above, we can rewrite these equations as

$$c_i = b_i - \left[\frac{1}{(n_i - 1)\frac{g_i(b_i)}{1-G_i(b_i)} + \prod_{j \neq i} n_j \frac{g_j(b_i)}{1-G_j(b_i)}} \right]$$

for class i bidders. These three equations provide nonparametric identification of the model as pseudo-costs can be recovered from estimates of the right-hand side objects which depend only on observed bid and auction-composition data. This argument is more direct than that of Flambard and Perrigne [2006] who observed reserve prices which were used in their snow-removal auctions. Essentially this identification strategy can be seen as an application of Theorem 3.1 of Athey and Haile [2007] in which identities are needed only to assign an appropriate class to each bidding firm.

4.2 Practical Estimation Issues

We consider estimation of this model by adopting the two-step nonparametric estimation procedure as suggested by GPV and extended by Flambard and Perrigne [2006]. In particular, in the first step we estimate the bid distributions and densities which allow us to recover a pseudo cost corresponding with each observed bid; in the second step we recover the latent cost densities. In each step we use nonparametric estimators which have been boundary corrected as suggested by Hickman and Hubbard [forthcoming]; thus, we adopt a boundary-corrected GPV (BCGPV) approach. In what follows we discuss some practical issues that arise when confronting the above model with real-world data.

A common practice in estimating a symmetric IPVP model is to assume the number of potential bidders equals the number of actual bidders and then restrict attention to all n-bidder auctions. Note that this assumption is not even valid for a fixed n in an asymmetric model as the composition of n-bidder auctions is likely changing based on how many bidders are from each class. For example, the bidding strategy of a class 0 bidder at an auction with two other class 0 bidders and two class 1 bidders is different than the bidding strategy of a class 0 bidder at an auction with four class 1 bidders, although the total number of bidders is the same at these auctions ($n = 5$). Thus, the "binning" approach suggested by Athey and Haile [2007] requires estimation be done separately for each set $\mathcal{N} = \{n, n_0, n_1, n_2 | n = n_0 + n_1 + n_2\}$. This is the downside of allowing flexibility and the cause for the dimensionality issues discussed earlier.

Specifically, first-step estimates $\left\{\hat{G}_0(b;\mathcal{N}), \hat{g}_0(b;\mathcal{N}), \hat{G}_1(b;\mathcal{N}), \hat{g}_1(b;\mathcal{N}), \hat{G}_2(b;\mathcal{N}), \hat{g}_2(b;\mathcal{N})\right\}$ must be constructed independently using only the bids from a given class over the set of $\mathcal{N}$ auctions. Thus, the bid distributions are estimated using empirical distribution functions

$$\hat{G}_i(b;\mathcal{N}) = \frac{1}{T_{\mathcal{N}}} \sum_{t=1}^{T_{\mathcal{N}}} \frac{1}{n_i} \sum_{\ell=1}^{n_i} 1(b_{i\ell t} \leq b),$$

where 1(A) is an indicator function that equals one if event A is true, and zero otherwise. The number of auctions $T_{\mathcal{N}}$ represents the number of auctions in the sample for which $\mathcal{N}$ is fixed and involves n_i bidders of class i. Thus, the observed bid $b_{i\ell t}$ represents the ℓth bid from a class i player at auction t which comes from a sample of $T_{\mathcal{N}}$ auctions in which (n, n_0, n_1, n_2) is the same for all auctions in this subsample. Our notation nests the symmetric model for a given n in which case $\mathcal{N} = \{(n, n, 0, 0), (n, 0, n, 0), (n, 0, 0, n)\}$. This is of practical importance as we often observe auctions with only class 0 bidders. Likewise, we estimate the bid density via

$$\hat{g}_i(b;\mathcal{N}) = \frac{1}{h_i^{\mathcal{N}} T_{\mathcal{N}}} \sum_{t=1}^{T_{\mathcal{N}}} \frac{1}{n_i} \sum_{\ell=1}^{n_i} \kappa\left(\frac{b - b_{i\ell t}}{h_i^{\mathcal{N}}}\right)$$

where κ is a boundary-corrected kernel function as suggested by Hickman and Hubbard [forthcoming] and $h_i^{\mathcal{N}}$ is a class-specific bandwidth that will be different for different sets $\mathcal{N}$. We adopt the mean-integrated-squared-error-minimizing rule applied to the kernel function $\kappa(\cdot)$ as suggested by Silverman [1986].

After obtaining estimates of $\left\{\hat{G}_0(b;\mathcal{N}), \hat{g}_0(b;\mathcal{N}), \hat{G}_1(b;\mathcal{N}), \hat{g}_1(b;\mathcal{N}), \hat{G}_2(b;\mathcal{N}), \hat{g}_2(b;\mathcal{N})\right\}$ we recover pseudo costs

$$\hat{c}_{i\ell t} = b_{i\ell t} - \left[\frac{1}{(n_{it}-1)\frac{\hat{g}_i(b_{i\ell t};\mathcal{N})}{1-\hat{G}_i(b_{i\ell t};\mathcal{N})} + \prod_{j\neq i} n_{jt}\frac{\hat{g}_j(b_{i\ell t};\mathcal{N})}{1-\hat{G}_j(b_{i\ell t};\mathcal{N})}}\right] \tag{2}$$

for class i where n_{jt} denotes the number of class j bidders at auction t such that $n_t = n_{0t} + n_{1t} + n_{2t}$ and $(n_t, n_{0t}, n_{1t}, n_{2t}) \in \mathcal{N}$. Note, too, that all pseudo costs are valid—boundary correction avoids the need to trim pseudo costs corresponding with bids observed within a bandwidth of the extremes of the sample.

The second step is more direct as the observed bids required us to account for different bidding strategies, even for a particular class of bidders depending on the composition of the bidders at auction, which required a binning procedure. Given our focus on a model within the IPVP, the recovery of the pseudo costs strips the composition effects from the model providing us with three independent samples of costs each from a respective density. As such, second-step estimation of the latent cost distributions is much easier because, for a given class, we can pool data from auctions not only across $\mathcal{N}$ for a given number of bidders n, but also across all the realized values of n in the sample (an issue we've, admittedly, not formally recognized until now to avoid complicating our notation). Specifically, take the sample of class-i pseudo costs $\{\hat{c}_i\}$ and estimate the cost density via

$$\hat{f}_i(c) = \frac{1}{T_i}\sum_{t=1}^{T_i}\frac{1}{n_{it}}\sum_{\ell=1}^{n_{it}}\frac{1}{h_i^c}\kappa\left(\frac{c-c_{i\ell t}}{h_i^c}\right)$$

where h_i^c is a second-step class-i bandwidth, κ is, again, a boundary-corrected kernel function, and now T_i represents the total number of auctions observed in the sample (across all $\mathcal{N}$) involving at least one class i bidder and n_{it} represents the number of class i bidders at auction $t \in \{1, 2, \ldots, T_i\}$.

The model and theory underneath the presentation above is built on the assumption that the contract at auction is identical and that the variation across observed bids is driven by variation in the cost draws of the bidding firms, which allows for the latent cost distributions to be identified from the observed bids. In real-world data, however, there is heterogeneity across the objects at auction.

In our application, we have data from a wide range of contract types and so it is important to control for many auction-specific characteristics. Recall the statistical importance of project size, project complexity, and project length in the bid regressions reported in Table 4. Moreover, the engineer's cost estimate is always statistically significant and accounts for why so much of the variation in observed bids is explained by the set of controls considered. Note too that many bidder-specific features were significant in those regressions. To control for factors other than the latent costs that will generate different bids, we homogenize the bids by first running a regression of the form:

$$b_{i\ell t} = \alpha(n_0, n_1, n_2) + \Gamma(\mathbf{x}_t, \mathbf{y}_\ell) + \varepsilon_{i\ell t}. \tag{3}$$

In this specification, $b_{i\ell t}$ is the ℓth bid tendered (by a firm from class i) at auction t, normalized by the engineer's estimate for auction t. We parameterize $\alpha(n_0, n_1, n_2)$ by considering auction-composition indicator variables which are specific to the number of bidders tendering offers from each of the three classes we observe. The function Γ depends on both contract-specific and bidder-specific components, which were employed in the regressions from Section 2 of the paper. We do not, however, include any LINC-related dummy variables as uncovering any potential differences in the cost distributions is our objective in this structural approach. The $\varepsilon_{i\ell t}$ represent private information, such as an idiosyncratic cost component for firm ℓ on contract t which is class-specific. We construct homogenized bids by combining the estimated bidder composition effects with the residuals; that is $\hat{b}_{i\ell t} = b_{i\ell t} - \Gamma(\mathbf{x}_t, \mathbf{y}_\ell)$. This homogenization process has been applied by other researchers—for an early approach see Pesendorfer [2000] and for a recent application see Bajari et al. [2014].

The advantage of this style of approach relative to an alternative suggested by GPV which kernel smooths over the covariates is that it reduces the dimensionality and enables one to control for many auction-specific characteristics without increasing the sample size. This, of course, requires additional structure be imposed concerning how covariates affect costs. Following Haile et al. [2006], we assume additive (or multiplicative, log-additive) separability in these elements which is attractive in that the additivity is preserved by equilibrium bidding, meaning the effects of the covariates can be controlled for via a regression of the observed bids on the covariates as suggested by equation (3).[24] Haile et al. accommodated endogenous participation and unobserved heterogeneity in a symmetric setting by constructing an index of unobserved heterogeneity using a participation equation. The key assumption is that there is a one-to-one mapping between the unobserved heterogeneity and the number of observed bidders at auction.[25] This allows for the estimation of an auction-specific index, which can then be included in the bid homogenization stage in a flexible way to address unobserved heterogeneity.

For reasons we have discussed, when an asymmetry is important the aggregate number of bidders is not the only important thing as the composition of bidders also induces different behavior in equilibrium. In our three-class case then, adopting an approach in the spirit of Haile et al. [2006] requires a one-to-one mapping between (n_0, n_1, n_2) and the unobserved heterogeneity factor(s). If there is only one auction-level unobservable, participation for each class of bidder would need to adhere to the same process (perhaps differing by scale). If there are class-specific unobservables, a formal aggregation assumption would be required. Moreover, it is not clear that there are important gains from inclusion of both the number of bidders and the unobserved heterogeneity indexes in the bid homogenization stage. Specifically, flexibly conditioning on (n_1, n_2, n_3) in the bid regression should be equivalent to conditioning on (n_1, n_2, n_3) plus the unobserved heterogeneity indexes. That is, the variance of the residual from such a regression should be the variance relevant for the GPV-based estimation conditional on (n_1, n_2, n_3) and the unobserved heterogeneity.[26]

[24] Haile et al. [2006] admitted this is a strong, but often employed assumption and that it may be more natural when valuations (costs) are normalized by an engineer's estimate, something we have done. Krasnokutskaya [2011] suggested a nonparametric procedure to recover the distribution of private costs in the presence of unobserved heterogeneity when the bidders' costs are the product of a common cost component and an individual cost component.

[25] The number of firms that bid is assumed to be an increasing function of the unobserved heterogeneity so that a participation equation can be inverted to recover the unobserved heterogeneity index. Roberts [2013] makes a similar assumption by considering reserve prices to be monotonically related to the unobserved heterogeneity.

[26] We view this as more palatable than imposing some ad hoc structure about class-specific responses to unobserved heterogeneity (which likely require some implicit assumptions about aggregation and scale). Presumably, Haile et al. [2006] obtained useful structure out of the symmetric model, which is why they chose to include both the unobserved heterogeneity and the number of bidders in the bid homogenization stage as this line of reasoning applies to that setting as well. It is less clear that these structural gains hold in the asymmetric setting, but obvious that more stringent assumptions are needed so instead, we argue that flexibly conditioning on (n_1, n_2, n_3) in the bid regression is sufficient.

5 Structural Estimates and Results

As described above, we partitioned (binned) our data by $\mathcal{N}$. Table 9 provides some insight into which bins are reasonable, sample-size wise, to use in nonparametric analysis. Specifically, Table 9 indicates that the majority of our auctions are symmetric auctions involving only ineligible bidders. We discard six auctions involving only LINC-graduate bidders and four auctions with LINC-eligible but untrained firms only, all of which involved two bidders at auction. There are a good deal of asymmetric auctions involving two or more bidders, but very few of them involve all three classes of bidders. The column "$n_1 = 0$" represents ineligible (class 0) bidders and LINC-trained (class 2) bidders both present at auction. The column "$n_2 = 0$" represents auctions involving ineligible (class 0) and LINC-eligible, but untrained (class 1) bidders. Ignoring auctions with a bidder from each class means each auction in the data will involve bidders representing no more than two classes. As such, one could construct matrices with the number of bidders at auction along the rows and the number of class 1 or class 2 bidders along the columns. Doing so, indicates that nearly all of the asymmetric auctions involve only one bidder from the LINC-related classes. Thus, we discard auctions with more than one of the LINC-related class bidders at auction.[27] We restrict attention to settings involving two to seven bidders as this ensures that there are at least 50 observations for every possible $\mathcal{N}$-bin needed for first-step estimation.[28]

[27]Remember, first-stage estimation is the most constraining data-wise for us as it must be done for each realization of $\mathcal{N}$.

[28]As discussed, the number of auctions for each instance in Table 9 is slightly lower than we've presented after we throw out the $n_1 > 1$ and $n_2 > 1$ asymmetric auctions. The minimum number of observations (50) corresponds to the number auctions involving six ineligible bidders and one class 1 bidder, for which we observe $50 \times 6 = 300$ class 0 bids and we have 50 observations from class 1 bidders. In addition, due to some extreme observations, we discard auctions having a bid in the top or bottom one percent of all homogenized bids. The number of observations reported in Table 9 and our discussion reflects observations post removal of auctions with bids at the extreme.

Table 9: Partitioning the Data by Symmetric vs. Asymmetric Auctions

Number of Bidders	Number of Auctions					
			Asymmetric			
	Total	Symmetric Non-LINC	Total	Ineligible v Trained $n_1 = 0$	Ineligible v Untrained $n_2 = 0$	All 3
2	1085	906	169	66	102	1
3	1600	1197	403	182	202	19
4	1379	896	483	241	222	20
5	1028	609	419	206	180	33
6	751	393	358	200	129	29
7	434	196	238	129	75	34

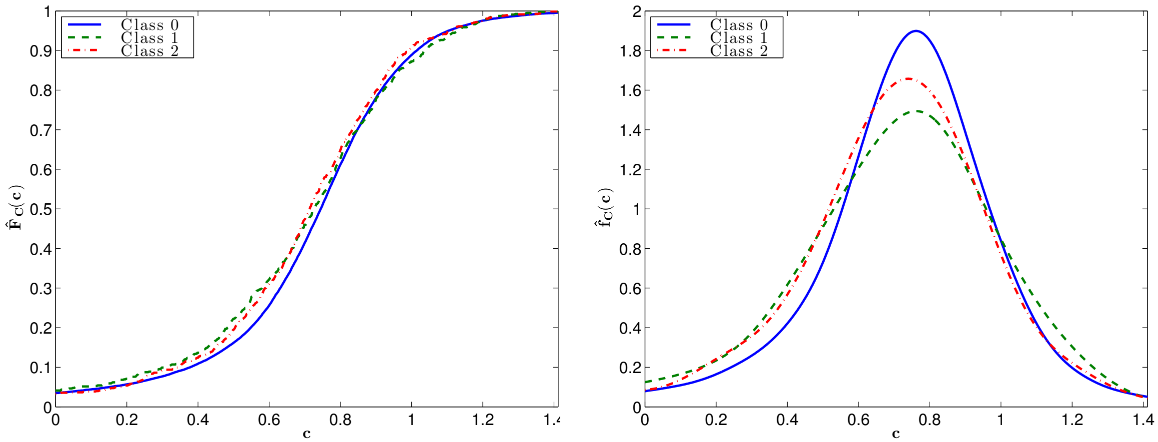
In both steps of the estimation we used the triweight kernel

$$\kappa(u) = \frac{35}{32}(1-u^2)^3 1\{|u| \leq 1\}$$

within a boundary-corrected estimator. We present the estimated cost distributions and cost densities in Figures 2a and 2b, respectively. There is no clear stochastic dominance relationship—further evidence of the crossing distributions of interest to Kirkegaard [2009] as well as Hubbard et al. [2013]. Because the curves are hard to distinguish we provide the quantile values of the pseudo costs in Table 10 which again shows that different classes look most favorable at different percentiles. We see the LINC-trained firms have the most attractive cost distribution from the 40th percentile through the 90th percentile. The upper half of the cost distribution corresponds with high cost types so perhaps these firms stand to gain the most from the LINC program.

Table 10: Deciles of the Estimated Cost Distributions

Percentile	Ineligible (class 0)	LINC-Qualified, but Untrained (class 1)	LINC-Trained (class 2)
10	0.38	0.31	0.34
20	0.55	0.48	0.50
30	0.63	0.58	0.59
40	0.69	0.66	0.66
50	0.74	0.73	0.71
60	0.79	0.79	0.78
70	0.85	0.85	0.83
80	0.91	0.92	0.90
90	1.01	1.04	0.99



(a) Estimated Cost Distributions

(b) Estimated Cost Densities

Figure 2: Estimates of Latent Cost Distributions and Densities

The estimated densities show that the modal cost of each class is quite similar. The LINC-trained bidders appear to have less variance in their latent cost distribution relative to those eligible, but untrained peers (indeed the standard deviation of the pseudo costs is 0.32 for the trained bidders and 0.35 for the untrained bidders). To test where there is a statistical difference between pairs of the cost distributions, we considered two-sample Kolmogorov–Smirnov tests in which the null hypothesis is that the cost distributions of the classes of firms being considered come from the same distribution, against an alternative that the two samples come from different distributions. The results of these tests are presented in Table 11. The cost distribution of ineligible firms is significantly different from both groups of LINC-related bidders at any standard test size, though the two LINC-related cost distributions are not significantly different from one another.

Table 11: Two-Sample Kolmogorov–Smirnov Tests for Asymmetric Cost Distributions

Hypothesis	KS Test Statistic	p-value
H_0: $F_0(c) = F_1(c)$; H_1: not H_0	0.0782	0.0002
H_0: $F_0(c) = F_2(c)$; H_1: not H_0	0.0661	0.0008
H_0: $F_1(c) = F_2(c)$; H_1: not H_0	0.0439	0.3816

We summarize the auction outcomes in Table 12. While the patterns we observe are consistent

Table 12: Summary of Auction Outcomes

		All	Symmetric Non-LINC	Ineligible v Trained ($n_1 = 0$)	Ineligible v Untrained ($n_2 = 0$)
$n = 2$	Total # auctions	1074	906	66	102
	Share Ineligible wins	0.92	1.00	0.52	0.50
	# inefficient	8	0	2	6
	Mean homog. rel. win. bid	0.81	0.81	0.77	0.82
	Mean Lerner's index	0.37	0.37	0.42	0.39
$n = 3$	Total # auctions	1552	1197	169	186
	Share Ineligible wins	0.93	1.00	0.70	0.65
	# inefficient	5	0	1	4
	Mean homog. rel. win. bid	0.75	0.76	0.74	0.71
	Mean Lerner's index	0.26	0.25	0.28	0.28
$n = 4$	Total # auctions	1308	896	225	187
	Share Ineligible wins	0.91	1.00	0.76	0.67
	# inefficient	4	0	2	2
	Mean homog. rel. win. bid	0.73	0.73	0.71	0.72
	Mean Lerner's index	0.22	0.23	0.23	0.21
$n = 5$	Total # auctions	947	609	185	153
	Share Ineligible wins	0.93	1.00	0.81	0.78
	# inefficient	5	0	5	0
	Mean homog. rel. win. bid	0.71	0.71	0.69	0.72
	Mean Lerner's index	0.19	0.18	0.22	0.19
$n = 6$	Total # auctions	671	393	174	104
	Share Ineligible wins	0.91	1.00	0.78	0.81
	# inefficient	1	0	1	0
	Mean homog. rel. win. bid	0.70	0.71	0.67	0.70
	Mean Lerner's index	0.17	0.17	0.18	0.20
$n = 7$	Total # auctions	360	196	114	50
	Share Ineligible wins	0.93	1.00	0.85	0.84
	# inefficient	1	0	1	0
	Mean homog. rel. win. bid	0.68	0.69	0.65	0.67
	Mean Lerner's index	0.17	0.15	0.18	0.18

with theory, they show little evidence of any type of clear evolution a LINC-qualified firm might make once it participates in the LINC program. Specifically, the share of wins garnered by the LINC-eligible firms is decreasing in the number of auction participants which makes sense given our need to focus only on auctions with one LINC-qualified firm; thus, increasing the number of bidders means increasing the share of bidders that are ineligible and reduces the likelihood of a LINC-qualified firm winning. Remarkably, there are relatively few inefficiencies realized in the data given the number of auctions conducted (only 24 of nearly 6000 auctions). They are split equally with twelve of them involving asymmetric auctions at which untrained bidders were present and twelve involving trained bidders at auction. Winning bids (relative winning bids which have been homogenized) are non-increasing as the competition increases. Having recovered an estimate of each firm's cost also allows us to look deeper at the effect of market power in this procurement industry. Specifically, we computed Lerner's index for each winning bidder observed in the data by computing $(b_t - \hat{c}_t)/b_t$. This is typically difficult to estimate in large part because costs are unobserved. Again, markups are not different across LINC-trained versus untrained bidders but our findings do show a decline in the mean Lerner's index within columns of the table as the level of competition increases. The last type of effect we look for LINC to have on firms in the market is in their propensity to remain active in the market, something we investigate in the next section.

6 Firm Survival

To consider longer-term effects that the LINC program might generate, we also consider firm exit patterns. Specifically, we estimate a probit model in which the response variable takes on a value of one if a given firm exits the industry in a given period, and takes on a value of zero otherwise. The challenge in such an exercise is identifying when a firm exits the market. With this in mind, we first discuss some choices we made in our investigation. First, 75% of the projects are completed in seven months. As such, we drop firms that entered the industry (firms that hold plans for the first time) after 2007 from the analysis given that we have an insufficient amount of time after that point to observe an exit. Second, we restrict attention to firms that entered the market after the LINC program was initiated so that all eligible firms in consideration had the opportunity to complete LINC training. Third, our exit date or the last active day in the TxDOT market is defined as the last date a firm held a plan or the last date they had an active project. Given that we do not use entrants after 2007 this gives us an opportunity to track bidders for at least 10 months since they last held plans or since their last active project day to ensure that they do not hold plans again within at least 10 months. Similar exit criteria were used by De Silva et al. [2009].

In Table 13, we present results from some of the probit regression models described above. Consistent with our previous work, in all models, the omitted class of firms is the group that is not eligible for the LINC program. The first three models consider all firms in the data and differ in how a firm's experience is captured. In each model, being eligible for the LINC program, but not having undergone training, increases the likelihood of a given firm exiting relative to the ineligible group by 0.6%. Though this effect is small, it is statistically significant at the 1% level and robust across these three specifications. In contrast, firms that graduate from the LINC program are not statistically different from non-LINC firms when it comes to exit. If the analysis is restricted to the LINC-qualified firms only, LINC training has no significant effect on a firm's survival. The other covariates included capture a firm's size (maximum backlog), competition in the market (based on how many rivals a firm has faced for a given month), economic conditions in Texas (the unemployment rate), and expectations about the volume of projects to be let. Larger firms are less likely to exit, while firms facing many rivals are more likely to exit—though if the rivals are LINC-trained then the firm is less likely to exit. These effects are all robust across specifications and significant at the 1% level.

Table 13: Exit Results

Variables	Exit Patterns for Entrants since 2001			
	All			LINC
	(1)	(2)	(3)	(4)
LINC-qualified, but untrained firm (β_1)	0.006***	0.006***	0.006***	
	(0.002)	(0.002)	(0.002)	
LINC-trained firm (β_2)	0.004	0.004	0.003	-0.002
	(0.003)	(0.003)	(0.003)	(0.004)
Past winning-to-bidding ratio	-0.001			0.005
	(0.003)			(0.007)
Past winning-to-plan holder ratio		0.001		
		(0.004)		
Past bidding-to-plan holder ratio			-0.010***	
			(0.002)	
Log (maximum backlog + 1)	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Log(total number of rivals faced	0.021***	0.021***	0.021***	0.024***
in the market + 1)	(0.001)	(0.001)	(0.001)	(0.002)
Log(total number of LINC rivals	-0.015***	-0.015***	-0.015***	-0.024***
faced in the market + 1)	(0.004)	(0.004)	(0.004)	(0.005)
Unemployment rate	0.002**	0.002**	0.002**	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Three month average of the real	0.003	0.003	0.003	-0.001
volume of projects	(0.002)	(0.002)	(0.002)	(0.006)
Number of observations	32,448	32,448	32,448	3,661
Pseudo R^2	0.530	0.530	0.534	0.589
Wald χ^2	3,433.83	3,440.000	3,322.670	415.950

Robust standard errors are given below point estimates in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

7 Conclusion

We considered an eclectic approach to investigate the effects of the TxDOT's LINC program from different perspectives. Some broad take-aways of our results are that firms that opt for LINC training are typically less experienced and face many rivals in the market. After completing LINC training, graduates are not too different from the larger set of LINC-qualified firms when it comes to their likelihood of entering an auction once they hold plans nor more likely to win once they've entered. That said, LINC graduates are more aggressive in their bidding behavior than ineligible firms and LINC-qualified, but untrained firms. The average LINC bid is 1.7% lower than that of ineligible firms and 2.9% (or 4.5% in one model) lower than that of LINC-qualified, but untrained firms. Moreover, winning bids from LINC-trained firms are 2.6% lower than bids from ineligible firms. How to reconcile this with the fact that LINC firms are no different from other firms in their chances of winning an auction once they've bid? We found LINC training had spillover benefits in the form of an indirect competition effect—on average, other firms bid more aggressively when a LINC firm expresses interest in a project. The combined effects of this more aggressive bidding has led to massive savings for TxDOT relative to the cost of operating the program. A concern might be whether firms can continue to operate in this way. While eligible firms have cost distributions that are statistically not any different from each other, the variance of costs for trained firms is a little lower than that of untrained firms. Our structural analysis also suggested that LINC-trained firms have Lerner indexes that are on par with that of other firms. Our firm survival analysis suggested that LINC-qualified, but untrained firms are more likely to exit in a given period than ineligible firms, but that this effect is not significant after LINC training.

Researchers have focused attention on bidder preference policies and subcontracting goals. A commonality between our work and this line of research is the targeted firms—LINC-qualified firms in Texas would typically qualify for such treatment in other states. From a policy perspective, our results suggest that such bidder training programs should be seriously considered by other states. As we noted, about 3/5 of U.S. states have a similar program in the works or already in place.

There are a few ways in which we hope others can apply and potentially extend our research. First, data on firm participation in specific aspects of a given program could provide researchers with a source of variation which would allow for identification of the aspects of a particular program that are most valuable. Second, these programs differ across states which we hope will allow for other investigations which may or may not differ in spirit from ours. In the Texas program, mentoring is completed by TxDOT officials but some states have programs that involve mentor firms paired with program participants. When talking with representatives from other states, a common challenge seemed to be getting participation from mentor firms (some states, like Ohio, require a minimum number of hours from the mentor each month and independent quarterly reports from both the mentor and protégé). If mentoring firms were seen in the data, one could quantify any improvement in mentor-firm performance after participating in the program.

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8 Appendix

Table 14: Variable Definitions.

Variable	Definition
Log of bids	Logarithm of bids
Entrant	Any firm that is a first time plan holder since the beginning of fiscal year 2001 in TxDOT auctions are considered as an entrant.
LINC-qualified, but untrained firms	Dummy to identify LINC-qualified, but untrained firms.
LINC-trained firms	Dummy to identify LINC-trained firms.
Number of plan holders	Number of firms that hold plans for a project prior to submitting bids.
Number of bidders	The number of bidders in an auction.
Log of engineer's estimate	The log value of the engineer's cost estimate.
Complexity	The total number of bid items (components) in a project.
Calendar days	Number of days to complete the project which is assigned by TxDOT
Ongoing project in the same county	This dummy variable identifies bidders when they are bidding on projects where they have an ongoing project in the same county.
Distance to the project location	The distance between the county the project is located in and the county of the firm's location.
Backlog	Backlog is constructed by summing the non-completed value of outstanding contracts. The backlog variable is similar to the variables used by Bajari and Ye (2003) and Jofre-Bonet and Pesendorfer (2003).
Capacity utilized	The utilization rate is the current project backlog of a firm divided by the maximum backlog of that firm during the sample period. For firms that have never won a contract, the utilization rate is set to zero.
Number of rivals faced in the market	This is the total number of unique plan holders faced in given month by a firm.
Number of LINC rivals faced in the market	This is the total number of unique LINC-qualified rivals faced in given month by a firm.
Past winning-to-bidding ratio	The number of previous wins divided by the number of previous bids at a point in time.
Past winning-to-plan holder ratio	The number of previous wins divided by the number of previous plans held at a point in time.
Past bidding-to-plan holder ratio	The number of previous bids divided by the number of previous plans held at a point in time.
Number of past bids	The number of previous bids a firm has submitted.
Average rivals' winning-to-plan holder ratio	The measure of rivals' past average success in auctions is constructed as the average across rivals of the variable "Past winning-to-plan holder ratio." This variable incorporates two aspects of past rival bidding behavior: the probability of a rival bidding given they are a plan holder and the probability the rival wins an auction given that they bid. These probabilities are initialized using data from 1997 and are updated monthly using the complete set of bidding data.
Unemployment rate	The monthly state-level, seasonally-unadjusted unemployment rate from the U.S. Bureau of Labor Statistics.
Material shares of a project	We identify six material groups for projects based on bid items described by the "Standard Specifications for Construction and Maintenance of Highways, Streets, and Bridges" code book adopted by TxDOT. These six material cost shares are constructed from detailed information on bid items and the project's overall engineering cost estimate. These include: 1) asphalt surface work (i.e., hot-mix asphalt); 2) earth work (i.e., excavation); 3) miscellaneous work (i.e., mobilization); 4) structures (bridges); 5) subgrade (i.e., proof rolling); and 6) lighting and signaling work (i.e., highway sign lighting fixtures).
Division dummies	TxDOT has 25 locational divisions in the state, which are identified by these dummy variables.